VISIBILITY ESTIMATION BASED ON CAMERA DATA AND WEATHER PARAMETERS

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Background

Finnish Meteorological Institute (FMI) has studied together with Jyväskylä University of Applied Sciences (JAMK) how to estimate visibility on the roads based on camera data. Camera data can be for example a still picture from road weather camera or video data from car's dash board camera. JAMK has used neural network technology to estimate the level of visibility from camera data.

The idea is to classify the observed visibility into three classes (normal, poor and very poor) and clarify the reason for the reduced visibility (snowfall, sleet, drifting/blowing snow on the road surface). Also, weather observations has been used to identify the precipitation form (snow, sleet or rain). Fog and rain are not included in to this study. In the meteorological point of view very poor visibility means that the horizontal visibility is 1000 meters or less.

Juga et al. have studied massive wintertime pile-up cases taken place in Finland [1, 2] and low visibility has played a significant role in those cases. Low visibility and icy road surface with low friction is a challenging combination for road safety. The aim of this study is to develop an image recognition system that could be used in targeted warnings about reduced visibility which can be delivered to drivers for example via wireless networks [3].

Neural network architecture and training process

Today terms like artificial intelligence (AI), machine learning (ML), and deep learning (DL) are big topics to deal for example big data. In this study, the deep learning algorithms are used to recognize the visibility from the images. Machine and deep learning algorithms can be used to building an approximate model of some function, such as extracting visibility from an image. The models are trained with a large dataset of training examples.

The algorithm relies on a convolutional neural network which is used to predict a single scalar (visibility) from the input image. Convolutional neural networks are one of the most widely used neural network models in image recognition and other image based regression tasks [4]. The main advantage of convolution layers is the ability to detect the same features independent of location within the input image.

A dataset of images with varying levels of visibility were chosen to train the network. A small portion of this dataset extracted to be the evaluation dataset, which was used to evaluate the performance of the network.

The rest of the data was used as training data. Only the image was used as an input: no other variables were used in predicting the visibility.

Due to the limited amount of training data and to avoid overfitting, several dataset augmentation techniques are used to grow the size of the dataset. Tools such as cropping, padding, rotation, flipping, contrast adjustment and random noise are used to alter the original training image data.

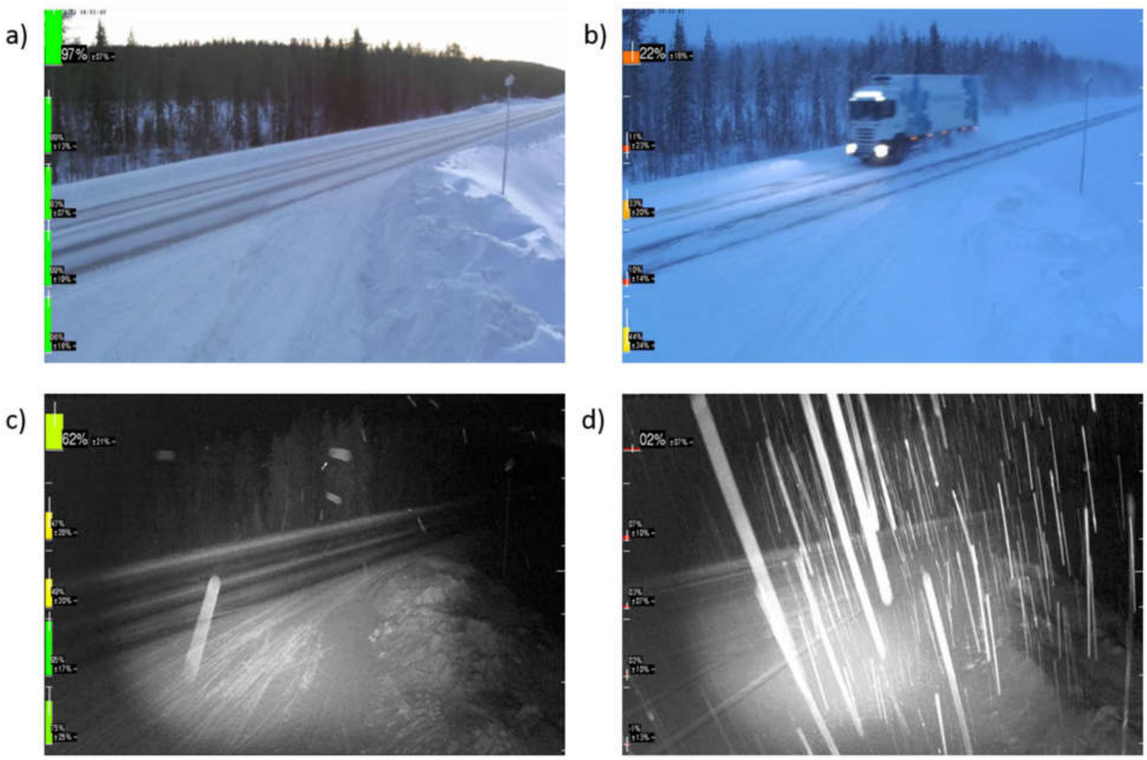

Fig. 1. *Different visibility classes based on neural network analyse of road weather camera pictures. Panel a) presents good visibility, b) very poor visibility (blowing snow), c) poor visibility (snowfall) and d) very poor visibility (snowfall).*

All of the networks were trained with Adam optimization algorithm with the suggested default settings [5]. All layers used Rectified Linear Unit, (ReLU) [6] as their activation function, other than the final fully connected layer which used no activation. The uncertainty quantifier [7] was implemented with the softplus activation function and the value for the lambda hyperparameter was chosen to be 3.25.

Results

Analysed visibilities from road weather camera picture are presented on figures 1a – 1d. Percent values on the left hand side present the relatively visibility, where 100 means good visibility and 0 very poor visibility. The percent value on top is an average of four different percent values analysed by using different neural network technique.

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